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DEVELOPMENT OF AN IMAGE SEGMENTATION METHOD FROM UNMANNED AERIAL VEHICLES BASED ON THE ANT COLONY ALGORITHM UNDER THE INFLUENCE OF SPECKLE NOISE

The object of research is the process of segmenting an image from an unmanned aerial vehicle based on the ant algorithm under the influence of speckle noise.

Unlike the known ones, the image segmentation method based on the ant algorithm involves the imitation of the collective behaviour of agents (ants) capable of adapting to local features of the image. In addition, the pheromone marking mechanism contributes to a more distinct delineation of the boundaries between segments, which positively affects the accuracy of dividing the image into segments.

Speckle noise is a type of multiplicative noise that occurs in images formed using coherent radiation. Its appearance is due to the interference of reflected waves coming from different points of the same object, but with microscopic differences in phase. This leads to the appearance of a chaotic granular structure that distorts the image and complicates further analysis.

Experimental studies have shown that the segmentation method based on the ant algorithm provides a reduction in segmentation errors of the first kind on average from 6% (in the absence of speckle noise) to 30% (at a speckle noise intensity $\sigma = 15$). With an increase in the speckle noise intensity, the gain in the value of the segmentation error of the first kind increases. The segmentation method based on the ant algorithm provides a reduction in segmentation errors of the second kind on average from 5% (in the absence of speckle noise) to 32% (at a speckle noise intensity $\sigma = 15$). With an increase in the speckle noise intensity, the gain in the value of the segmentation error of the second kind increases.

The practical value of the segmentation method based on the ant algorithm lies in the possibility of segmentation under the influence of speckle noise. At the same time, a reduction in segmentation errors of the first and second kind is ensured in comparison with the known method.

Keywords: *segmentation, unmanned aerial vehicle, ant algorithm, speckle noise, Sobel operator.*

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1. Introduction

The 21st century has seen the active introduction of unmanned aerial vehicles (UAVs) into various areas of human activity, from agriculture to defense [1]. Due to their mobility, accessibility, and ability to perform imaging in conditions inaccessible to traditional platforms, UAVs have become an indispensable source of data for environmental monitoring, cartographic creation, agricultural visualization, detection of objects on the ground, and other analytical tasks [2]. All of these applications involve the use of aerial photographs or video footage that require further processing. One of the key stages of analyzing the resulting visual data is segmentation, which is the process of dividing an image into structured regions that allows to isolate objects or areas of interest for further interpretation [3]. It has been established that the quality of segmentation largely depends on the level of noise in the input image [4]. In the case of UAVs, shooting takes place in conditions that are far from ideal, which leads to the appearance of various noises. Factors contributing to the appearance of distortions include [5, 6]:

– vibration loads on the aircraft, which can cause microshifts even in the presence of gyrostabilization;
– design limitations of the devices, which force the use of compact sensors with reduced characteristics;
– shooting in low light conditions, which increases the noise-to-signal ratio;
– compression of video or photo data in real time, which leads to the appearance of artifacts;
– influence of radio interference during signal transmission;
– operation of built-in image processing algorithms, which can create digital distortions.

The most common types of noise in images obtained from UAVs are additive white Gaussian noise, speckle noise, impulse noise, salt and pepper noise, color noise, compression artifacts, sampling noise, motion noise, dark noise, etc. [7]. Their appearance is due to both physical limitations of sensors and difficult operating conditions. Speckle noise deserves special attention, which is characteristic of coherent image sources or certain sensors, and significantly complicates segmentation due to its complex nature and high density [8].

In such conditions, there is an urgent need to create segmentation methods that would be resistant to various types of noise, in particular, speckle noise.

Therefore, the development of a method for segmenting images from UAVs under the influence of speckle noise is relevant.

Segmentation of images obtained from UAVs is currently one of the leading areas in the field of computer vision and digital visual data processing. With the growth of aerial photography and the need for automatic analysis of such images, the relevance of developing effective segmentation methods increases. Researchers pay special attention to the creation of algorithms that can effectively highlight objects in images that are affected by various interferences, including noise caused by shooting conditions, hardware limitations, or external factors. Solving this problem is critically important for improving the quality of data processing in applied areas such as environmental monitoring, the agricultural sector, defense, and emergency response. To perform segmentation of images obtained from UAVs, both classical segmentation algorithms and methods based on deep learning are currently used. The analysis showed that each of the approaches has its own advantages, limitations, and specific applications, especially in conditions of increased complexity of input data characteristic of aerial photographs.

Classical segmentation methods are usually based on processing pixel features, geometric or statistical properties of the image.

In [9], a classical *k*-means algorithm with validation metrics for automatic determination of the number of clusters in space images was proposed for image segmentation. At the same time, its efficiency depends on data preprocessing and parameterization, which requires careful tuning and evaluation of results in conditions of noise and uneven illumination. The main advantage of [9] is the balance of simplicity and validity, because the use of *k*-means allows for quick grouping of pixels, and valid indices provide an objective choice of the number of clusters, without the need for expert "by eye" selection. The disadvantage of [9] is limited resistance to noise and complex background structures.

In [10], a method for segmenting small aerial objects in optoelectronic images using one of the methods based on detector edges, namely the classical Sobel operator, is proposed. The advantage of [10] is its simplicity and speed of implementation, which makes it suitable for real-time applications on devices with limited computing capabilities. The main disadvantage of [10] is its sensitivity to noise: despite the pre-filtering, the Sobel operator can react to small changes in brightness caused by noise or artifacts. This reduces the accuracy of segmentation in difficult imaging conditions (e. g., low contrast or atmospheric interference).

[11] describes one of the simplest and fastest methods for dividing an image into regions (e. g., object/background) by comparing the intensity of each pixel with a certain threshold value. The advantages of [11] are high performance, ease of implementation, and good results in segmenting images with clear contrast between objects and background. That is, threshold segmentation is an effective basic tool for preprocessing or in well-controlled environments. However, for more complex UAV scenes, it is advisable to supplement it with more robust methods, such as adaptive thresholding or deep learning.

Common disadvantages of classical segmentation methods are their dependence on high-quality image preprocessing, high sensitivity to noise and lighting changes, and limited generalization ability in conditions of high data variability.

With the rapid development of deep neural networks, in particular convolutional neural networks (CNN), image segmentation has reached a new level of accuracy and robustness.

In [12], one of the first models that allowed pixel classification without fully connected layers was considered. The main idea is to replace fully connected layers with convolutional ones, which allowed working with images of arbitrary size, obtaining pixel predictions and storing spatial information. The main disadvantage of [12] is the slowness in segmenting large images and the difficulty in segmenting small details.

One of the most common architectures for segmentation is presented in [13]. Due to the symmetric structure (encoder–decoder) and the connections between the corresponding levels, it provides good localization of objects even under conditions of limited amounts of training data. The main disadvantages of [13] are high memory consumption, especially at high image resolution, sensitivity to class balance may require weight coefficients in the loss function and disregard for the global context outside the field of view.

In [14], an improved architecture of DeepLab v3+ is presented, which allows the model to work effectively with both global context and precise boundaries. Thanks to the global context (ASPP) and deep features, the model shows relative robustness to image noise. However, it is sensitive to significant artifacts or irregular noise if data augmentation is not applied. Another disadvantage of [14] is the need for large computational resources for training.

In [15], an improved architecture based on Mask R-CNN is presented. By using high-resolution semantic features, RefineMask copes better with noise, especially when object contours are blurred. However, disadvantages of [15] are the complicated architecture with more components compared to Mask R-CNN, higher memory and training time requirements, and the need for well-balanced training (in the refinement stages) to avoid overcomputing or loss of context.

Therefore, the general drawbacks of deep learning methods are the need for significant computational resources, the dependence on a high-quality and balanced training sample, and the vulnerability to "overtraining", especially on limited datasets.

The analysis showed that today one of the promising approaches in image segmentation is the use of metaheuristic algorithms. Metaheuristic algorithms are increasingly used for image segmentation due to a number of key advantages that distinguish them from traditional methods, namely:

– *adaptability to complex and heterogeneous data*. Metaheuristics do not require prior assumptions about the distribution of pixels or the shape of objects, which makes them suitable for images with noise, heterogeneity or weak contrast;
– *flexibility in choosing objective functions*. Segmentation criteria can be adjusted for a specific task (contrast, homogeneity, geometry, etc.);
– *global optimization*. Unlike gradient methods, metaheuristic approaches are able to avoid local minima and find more accurate solutions in complex feature spaces;
– *possibility of combining with other methods*. They are easily integrated with neural networks, classical image processing algorithms or post-processing (for example, for contour refinement);
– *high efficiency in multi-criteria tasks*. They allow to simultaneously optimize several indicators of segmentation quality (for example, accuracy of boundaries and homogeneity within clusters).

In [16], an approach to detecting objects in images based on the Firefly Algorithm is considered. This method models the natural behavior of fireflies, which move towards brighter individuals, which provides an effective mechanism for adaptive search in the solution space. Due to this, the algorithm is able to successfully find target objects even in complex scene conditions, bypassing local extrema. The main advantage of [16] is high accuracy and robustness to noisy and complex data. At the same time, the disadvantages of the method include significant computational costs and slowing down of convergence when the number of agents increases, which creates difficulties when scaling to large satellite images.

In [17], a method for segmenting images obtained from UAVs is described, which is based on the Particle Swarm Optimization algorithm. The proposed strategy allows for accurate detection and isolation of objects in aerial images due to the optimal adjustment of cluster positions

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during the segmentation process. The main advantages of [17] include high efficiency in processing complex and high-resolution images, since PSO is able to quickly find global extrema in a wide solution space. At the same time, among the disadvantages of [17], it is worth noting the sensitivity to initial conditions and parameters, which can lead to falling into local optima and a decrease in segmentation quality when changing the data type or environment. In [18], an approach to detecting object contours in structurally complex color satellite images is proposed, which is based on the Ant Colony Optimization (ACO) algorithm. This method simulates the natural path-finding strategy of ants, which allows for effective detection of clear object boundaries even under conditions of complex image texture. A significant advantage of [18] is the ability to perform global search, which provides high accuracy of contour extraction in complex scenes. However, the disadvantages of [18] include high computational complexity and execution time, which limits its application for large satellite images. Analysis of literature sources indicates that the approach proposed in [18] is promising for solving the problems of segmentation of aerial images, in particular those obtained from UAVs. As noted in [18], ACO demonstrates efficiency in global optimization of separation functions, which allows adapting the method to image processing with a high level of complexity and structural diversity. However, the use of ACO for processing "noisy" images remains understudied. This emphasizes the relevance of further experiments aimed at assessing the stability and accuracy of the algorithm in conditions of "noise pollution", which is of crucial importance for the practical application of UAV images.

The article considers a method for segmenting UAV images based on the ant algorithm, taking into account the influence of speckle noise, in order to increase the accuracy of detecting objects of interest.

The aim of research is to develop a method for segmenting UAV images based on the ant algorithm under the influence of speckle noise.

2. Materials and Methods

The object of research is the process of segmenting an image from a UAV based on the ant algorithm under the influence of speckle noise.

The following assumptions were made during the research:
– the image from a UAV is optoelectronic;
– the influence of speckle noise is considered;
– the influence of other distorting factors is not considered;
– the method based on the Sobel operator was chosen for comparison.

The following research methods were used:
– methods of digital image processing, artificial intelligence, neural networks, comparative analysis, synthesis and analysis – for the analysis of methods of segmenting an image from a UAV;
– methods of probability theory and mathematical statistics, optimization theory, digital image processing, swarm intelligence – for the development of a method of segmenting an image from a UAV based on the ant algorithm under the influence of speckle noise;
– methods of optimization theory, swarm intelligence, digital image processing, mathematical modeling, comparative analysis – when processing images from UAVs under conditions of speckle noise.

Used:
– hardware: Dell laptop Intel® Core™ i7-8650U CPU@ 1.90 GHz;
– software: object-oriented programming language Python 3.11, programming language Matlab 7 with application program package.

3. Results and Discussion

3.1. Main stages of the method of segmenting images from unmanned aerial vehicles based on the ant algorithm

When developing the main stages of the method of segmenting images from UAVs based on the ant algorithm, it is possible to rely on [19].

The method of segmenting images from UAVs based on the ant algorithm includes the following stages [19]:

1. *Initial setup*. The algorithm starts with determining the key parameters of the algorithm that regulate the behavior of agents (ants). This stage includes:
– selecting the number of agents (ants) in the system;
– determining the importance of the pheromone trail and heuristic factors;
– setting the pheromone extinction coefficient that supports the dynamic nature of the search;
– initializing the pheromone level on all paths (graph arcs);
– creating a graph structure of the image, where nodes are pixels and edges are possible transitions.

2. *Placing agents (ants)*. At this stage, agents are randomly placed at different points of the graph, providing an initial variety of routes. Each agent is tasked with finding a complete solution, avoiding repeated visits to pixels already visited.

3. *Formation of solutions*. Agents build routes step by step, focusing on the pheromone level and heuristic information (for example, proximity to other pixels). The transition to the next pixel occurs probabilistically, which allows to vary routes and avoid local minima.

4. *Evaluation of results*. After the routes are formed, their analysis is performed:
– the quality of the routes is assessed according to a certain criterion (for example, the length or homogeneity of segments);
– the most successful ones are saved for further analysis;
– based on the data obtained, the system behavior is adjusted in subsequent iterations.

5. *Updating the pheromone map*. Pheromones on the routes:
– partially evaporate, reducing the impact of less successful solutions;
– are updated according to the quality of the solutions found – better routes leave a stronger trace.

6. *Iterative processing*. The algorithm cyclically repeats the processes of constructing solutions and updating pheromones until the specified stopping conditions are reached (for example, the number of iterations or the absence of improvement).

7. *The result of the algorithm*. After completion of the work, the system returns the optimal solution, namely the division of the input image into segments taking into account the spatial structure of the scene.

As shown by the results of the research presented in the source [18], the use of the ant algorithm for the image segmentation problem provides high quality. Unlike the known ones, the method of image segmentation from a UAV based on the ant algorithm involves the imitation of the collective behavior of agents (ants) capable of adapting to local features of the image. In addition, the pheromone marking mechanism contributes to a more distinct delineation of the boundaries between segments, which positively affects the accuracy of dividing the image into segments.

3.2. Brief description of speckle noise affecting images from unmanned aerial vehicles

In real conditions, images from UAVs are distorted due to the presence of various types of noise. One of the most common is speckle noise, which has a multiplicative nature and arises as a result of the interference effect during image formation. Such distortions can be caused by the characteristics of signal reflection, receiver characteristics, or shooting conditions.

Analysis [20] shows that speckle noise has a significant impact on image processing results, in particular:
– reduction of image contrast, because due to the granular structure of speckle noise, it is difficult to recognize fine details and transitions between objects;
– blurring of boundaries between segments due to the fact that noise masks natural contours and, as a result, worsens the quality of segmentation and the accuracy of object localization;

– complication of pixel classification by intensity or texture characteristics due to reduced homogeneity within segments;
– appearance of pseudostructures – visual artifacts created by noise can be perceived by the algorithm as real elements of the scene, which leads to erroneous interpretation;
– reduction in the efficiency of feature detectors – filters of contours, gradients or textures can erroneously react to noise, increasing the probability of false positives;
– the need for additional filtering, because to improve the quality of the image before processing, preliminary noise suppression is often required, which, in turn, increases computational costs.

Speckle noise is a type of multiplicative noise that occurs in images formed using coherent radiation. Its appearance is due to the interference of reflected waves coming from different points of the same object, but with microscopic differences in phase. This leads to the appearance of a chaotic granular structure that distorts the image and complicates further analysis.

Unlike additive noise, speckle noise is multiplicative in nature, meaning the intensity of the distortion depends on the brightness of the signal itself. Therefore, speckle noise is represented as multiplicative noise

$$I_{noisy}(x,y)=I(x,y)\cdot N(x,y), \tag{1}$$

where $I(x, y)$ – the original image; $N(x, y)$ – a conditional coefficient (usually distributed according to the lognormal or gamma distribution, or as $(1+N(0,\sigma))$).

The standard deviation σ in this context is usually used to model the noise intensity. Its value directly determines the effect of speckle noise on the image:

1. *With a small standard deviation value* ($\sigma \approx 0.05$–0.1) – the speckle noise is almost invisible, the image remains clear, but there is a slight graininess on it.
2. *With an average standard deviation value* ($\sigma \approx 0.2$–0.3) – the image contrast deteriorates, visible graininess appears, small image details become less clear.
3. *With a large standard deviation value* ($\sigma \geq 0.4$) – the image is already severely distorted by intense noise, information is lost, and quality decreases.

Therefore, speckle noise, even at low standard deviation values, significantly reduces the visual quality of the image, masks important details, and complicates segmentation and object recognition.

3.3. Image segmentation using the ant algorithm-based method under speckle noise conditions

Experimental studies were conducted to verify the operation of the ant algorithm-based segmentation method under speckle noise conditions. Particular attention was paid to the method's resistance to speckle noise, which is typical for images obtained in real conditions. A comparative analysis of the segmentation results with the method [10] was also performed. This is an algorithm-based segmentation method.

An image from the DJI Mavic 3 Pro (DJI RC) (China) UAV was used as a test image (Fig. 1) [17, 21]. The main characteristics of the image are described in [17]. The image was captured with a wide-angle 4/3 Complementary Metal-Oxide-Semiconductor (CMOS) Hasselblad camera, 20 MP, RAW format, shooting speed 5.1 K/50 frames per second [17].

The test image (Fig. 1) shows a road scene with a vehicle and a trailer, which is partially covered by vegetation elements. Such partial visual masking complicates the process of accurate object segmentation. In the upper part of the image, background vegetation is observed along the roadside, which forms a complex textural structure and brightness gradient typical of the natural environment. This image was chosen as a reference example for testing algorithms for detecting and segmenting ground objects in real-world UAV applications. It is used as the main test image to verify the quality of the segmentation method based on the ant colony algorithm under the influence of speckle noise.

Fig. 1. Test image [17, 21]

When performing segmentation, by analogy with [17], the following initial data and assumptions were made:
– initial image – from the DJI Mavic 3 Pro (DJI RC) UAV (China);
– color space of the original image representation – Red-Green-Blue (RGB);
– object of interest – vehicle with trailer;
– size of vehicle with trailer is smaller than the size of background objects;
– the effect of speckle noise is considered;
– the effect of scaling and rotation of the original image is not considered;
– hardware: Dell laptop Intel® Core™ i7-8650U CPU@ 1.90 GHz;
– software: object-oriented programming language Python 3.11, programming language Matlab 7 with application program package.

Experimental assessment of the stability of the method based on the ant algorithm is carried out by artificially imposing noise distortions on the test image (Fig. 1). The study took into account two levels of speckle noise intensity: $\sigma = 5$ (Fig. 2) and $\sigma = 15$ (Fig. 3). This allows to analyze the performance of the method based on the ant algorithm at different degrees of noise pollution.

Fig. 2. Test image with superimposed speckle noise distortion ($\sigma = 5$)

Fig. 3. Test image with superimposed speckle noise distortion ($\sigma = 15$)

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Fig. 4–6 show the results of image segmentation using the ant algorithm method with different levels of noise exposure: without adding speckle noise (Fig. 4), with a noise level of σ = 5 (Fig. 5), and with a noise level of σ = 15 (Fig. 6).

Fig. 4. Segmented test image (Fig. 1) by the method based on the ant algorithm in the absence of speckle noise (σ = 0)

Fig. 5. Segmented test image distorted by speckle noise (σ = 5) (Fig. 2), processed by the method based on the ant colony algorithm

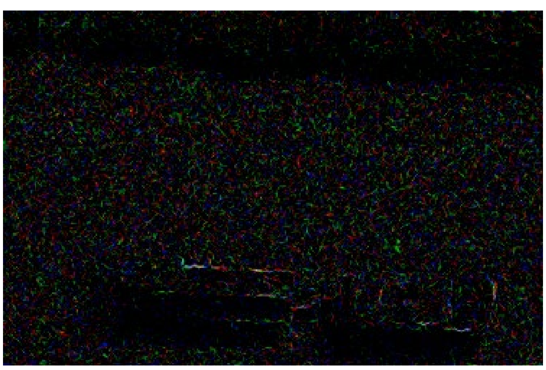

Fig. 6. A segmented test image distorted by speckle noise (σ = 15) (Fig. 3), processed by a method based on the ant colony algorithm

For comparative analysis, Fig. 7–9 demonstrate the results of segmentation of the same images by a method based on the Sobel operator [10]. In particular, Fig. 7 illustrates the result for an image without noise, Fig. 8 at a noise level of σ = 5, and Fig. 9 at a noise level of σ = 15.

Comparisons of the results shown in Fig. 4–9 allow to visually assess the quality of segmentation under conditions of varying degrees of noise pollution. The analysis covers two approaches: the segmentation method based on the ant algorithm and the well-known segmentation method based on the Sobel operator. Such a comparison allows to visually determine which of the methods provides a higher quality of segmentation of objects in images under the influence of speckle noise of different intensities.

However, visual analysis is not enough to objectively assess the quality of segmentation. Therefore, an additional quantitative assessment of the results was carried out, which is based on the assessment of segmentation errors of the first and second kind.

Fig. 7. A segmented test image that is not distorted by speckle noise (σ = 0) (Fig. 1), segmented by a method based on the Sobel operator

Fig. 8. A segmented test image distorted by speckle noise (σ = 5) (Fig. 2), segmented by a method based on the Sobel operator

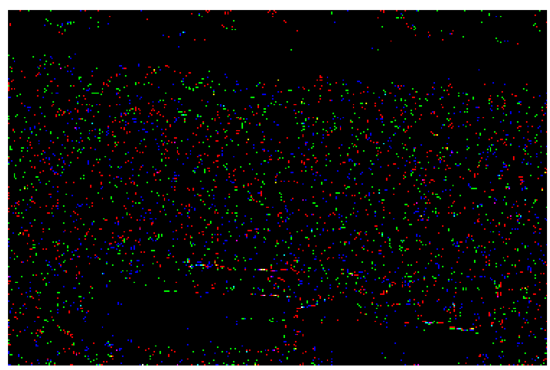

Fig. 9. Segmented test image distorted by speckle noise (σ = 15) (Fig. 3), segmented by the method based on the Sobel operator

To calculate segmentation errors of the first (α_1) and second (β_2) kind, expressions (2) and (3), respectively [17], are given:

$$\alpha_1 = \frac{S_1(fs(\mathrm{X}))}{S_2(f(\mathrm{X}))}, \tag{2}$$

$$\beta_2 = 1 - \frac{S_3(fs(\mathrm{X}))}{S_4(f(\mathrm{X}))}, \tag{3}$$

where $\mathrm{X}(x, y)$ – the vector of pixel coordinates in the image; $f(\mathrm{X})$ – the original image; $fs(\mathrm{X})$ – the segmented image; $S_1(fs(\mathrm{X}))$ – the number of background pixels incorrectly assigned to the object of interest in the image $fs(\mathrm{X})$; $S_2(f(\mathrm{X}))$ – the number of background pixels in the image f(X); S_3(fs(X)) – the number of correctly segmented pixels of the object of interest in the image fs(X); S_4(f(X)) – the number of pixels of the object of interest in the image f(X).

The results of calculating the segmentation errors of the first (α_1) and the second (β_2) kind are given in Table 1 and Table 2 in the absence of the influence of speckle noise ($\sigma = 0$). The image was segmented 5 times. The segmentation errors of the first (α_1) and the second (β_2) kind were calculated for the known method (the method based on the Sobel operator) and the method based on the ant algorithm.

Table 1

Segmentation error of the first kind (α_1)

Segmentation method name	Segmentation error of the first kind (α_1), %		
	Speckle noise intensity (σ)		
	$\sigma = 0$	$\sigma = 5$	$\sigma = 15$
Sobel operator-based method	27.6	66.8	93.7
Ant algorithm-based segmentation method	21.9	43.8	63.9

Table 2

Segmentation error of the second kind (β_2)

Segmentation method name	Segmentation error of the second kind (β_2), %		
	Image segmentation process number		
	$\sigma = 0$	$\sigma = 5$	$\sigma = 15$
Sobel operator-based method	25.3	62.8	91.2
Ant algorithm-based segmentation method	20.4	39.6	59.8

At the same time, segmentation errors of the first (α_1) (Table 1) and the second (β_2) kind (Table 2) are unchanged for the segmentation method based on the Sobel operator and do not depend on the number of segmentation processes.

Analysis of Tables 1 and 2 show that the segmentation method based on the ant algorithm provides a reduction in segmentation errors of the first kind on average from 6% (in the absence of speckle noise) to 30% (with speckle noise intensity $\sigma = 15$). With increasing speckle noise intensity, the gain in the value of the segmentation error of the first kind increases.

The segmentation method based on the ant algorithm provides a reduction in segmentation errors of the second kind on average from 5% (in the absence of speckle noise) to 32% (with speckle noise intensity $\sigma = 15$). With increasing speckle noise intensity, the gain in the value of the segmentation error of the second kind increases.

The practical significance of the segmentation method based on the ant algorithm lies in the possibility of performing segmentation under the influence of speckle noise. This ensures a reduction in segmentation errors of the first and second kind compared to the known method.

Research limitations:

– the segmentation method can be applied only to optoelectronic images;

– quantitative calculations of errors of the first and second kind can be applied to image segmentation only under the influence of speckle noise.

Prospects for further research: calculation of segmentation errors of the first and second kind under the influence of other distorting factors.

4. Conclusions

Unlike the known ones, the method of segmenting images from UAVs based on the ant algorithm involves imitating the collective behavior of agents (ants) capable of adapting to local features of the image. In addition, the pheromone marking mechanism contributes to a more distinct delineation of the boundaries between segments, which has a positive effect on the accuracy of dividing the image into segments.

Speckle noise is a type of multiplicative noise that occurs in images formed using coherent radiation. Its appearance is due to the interference of reflected waves coming from different points of the same object, but with microscopic differences in phase. This leads to the appearance of a chaotic granular structure that distorts the image and complicates further analysis.

The segmentation method based on the ant algorithm provides a reduction in segmentation errors of the first kind on average from 6% (in the absence of speckle noise) to 30% (at a speckle noise intensity of $\sigma = 15$). With increasing speckle noise intensity, the gain in the value of the first-order segmentation error increases.

The segmentation method based on the ant algorithm provides a reduction in the second-order segmentation errors on average from 5% (in the absence of speckle noise) to 32% (at a speckle noise intensity of $\sigma = 15$). With increasing speckle noise intensity, the gain in the value of the second-order segmentation error increases.

The practical value of the segmentation method based on the ant algorithm lies in the possibility of performing segmentation under the influence of speckle noise. At the same time, a reduction in the first and second-order segmentation errors is ensured compared to the known method.

Conflict of interest

The authors declare that they have no conflict of interest regarding this research, including financial, personal, authorship or other, which could affect the research and its results presented in this article.

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Data availability

Data will be provided upon reasonable request.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the presented work.

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